

Unpacking effective learning through game analytics

HABGOOD, Jacob <<http://orcid.org/0000-0003-4531-0507>>

Available from Sheffield Hallam University Research Archive (SHURA) at:

<http://shura.shu.ac.uk/18822/>

This document is the author deposited version. You are advised to consult the publisher's version if you wish to cite from it.

Published version

HABGOOD, Jacob (2018). Unpacking effective learning through game analytics. In: CHI 2018 Data-driven educational game design, Carnegie Mellon University, 21st April 2018.

Copyright and re-use policy

See <http://shura.shu.ac.uk/information.html>

Unpacking Effective Learning Through Game Analytics

M. P. Jacob Habgood

Sheffield Hallam University
Sheffield, United Kingdom
j.habgood@shu.ac.uk

Tim Jay

Sheffield Hallam University
Sheffield, United Kingdom
t.jay@shu.ac.uk

Martyn Mees

Sheffield Hallam University
Sheffield, United Kingdom
m.mees@shu.ac.uk

Paul-Howard Jones

University of Bristol
Bristol, United Kingdom
paul.howard-jones@bristol.ac.uk

Abstract

This paper describes how a data-driven design analysis was applied to the iterative development of a tablet-based mathematical game for the RAIDING Project. Detailed analytics were recorded for a class of 7-year old children who used the game once a day over a two-week period. Data was recorded to measure the proportion of time spent effectively engaged with learning content (effective learning time). Average response times and accuracies were recorded at the end of each day and plotted to reveal individual trends. This data alluded towards differences in behaviour which were not predicted by effective learning time, and which have prompted iterative changes in the design of the game.

ACM Classification Keywords

K.3.1 [Computers and Education]: Computer Uses in Education; K.8.0 [Personal Computing]: Games

Introduction

The RAIDING Project is investigating how game-based learning promotes children's mathematical cognition through the design and evaluation of an adaptive mathematics game for 7-year olds [6]. The space-themed game for Android tablets (figure 1) integrates mathematical tasks into the core mining game mechanic, in line with approaches to intrinsically integrated game design [3]. It also includes a meta-game which allows currency earned from mining to be spent on constructing a mothership in which players can collect and store alien lifeforms (figure 1). The game incorporates several novel design approaches taken from free-to-play game design, including sessioning and return triggers [5]. Sessioning uses resource limitations (limited mining carts) to encourage players to end their playing session before they become bored with playing the game. Return triggers provide players with an explicit reward for resuming play at a future point in time (alien eggs which hatch the next day). The game incorporates a learner model to drive the adaptive difficulty of the mathematical content. Critically, the game's design deliberately decouples mathematical difficulty from gameplay difficulty so that player advancement in the meta-game is based on effort rather than academic ability.

Background

Time-on-task has long been considered a key predictor of learning [2] and can be used as a measure of motivation in games [3], but there is some debate as to how it should be quantified [4]. An approach, for game-based learning put forward by Romero and Usart [7] makes the distinction between the total time-on-task and effective learning time (ELT) defined as, "the time the learner is successfully engaged in activities oriented towards learning objectives" (p. 250). This distinction has particular relevance to intrinsically integrated games which attempt to place learning content within the core gaming activity so that time-on-task is broadly equivalent to ELT [3]. Conversely, extrinsically integrated games typically separate learning content from gameplay so that ELT is inversely proportional to time spent engaged in core gameplay. Despite this key distinction, ELT for a specific game can also vary according to other factors, such as the time spent navigating the environment, learning the controls of the game or watching story-driven content. In the

case of RAIDING, the player spends a proportion of their time engaging with a non-mathematical meta-game, and so we were interested in measuring individual players' ELT and exploring if this was a predictor of learning outcomes.

Learner Model

The game's learner model drives the adaptive difficulty of the game in line with a chronometric model of learning focusing on reaction time [1]. The learner model begins empty, and only allows a restricted range of times tables tasks to be delivered. During play, the model records reaction time and outcomes for each task presented, maintaining a rolling average reaction time and accuracy score for each multiplier. As a player demonstrates mastery, the learner model unlocks a wider range of tables and reduces the frequency of the older ones. Mastery is determined by first demonstrating a high level of accuracy, then a response time of less than two seconds.



Figure 1: (left) The RAIDING game's core mathematical gameplay: mining rocks to earn currency. (right) The player's mothership which forms the basis of the (non-mathematical) meta-game.

The focus on response time in this model led the team to design an explicit game mechanic to motivate improvements in response time. For this feature, the player was given an additional sensory reward for tasks which were completed within the two second response time (rocks bursting into flames accompanied by the words "ON FIRE!"). Preliminary testing with children suggested that this feature was popular and made the game more motivating to play.

Method

As part of a wider study, 53 children played the RAIDING game for an average of 20 minutes a day, for 10 days within a two-week period. Pre and post-test measures of the children's mathematical ability were recorded using the Westwood 1 Minute Test. A large amount of analytical data was recorded by the game, including the state of the learner model at the end of each day and time-stamped logs recording the player's use of different parts of the game.

Measures and Hypotheses

Primary measures of interest to this investigation were:

- *Learning Gains*: difference in test scores between the start and the end of the study.
- *Effective Learning Time*: time playing maths mining games over the study (not the metagame).
- *Total Learning Tasks*: total number of maths tasks presented over the study (inc. distractors).
- *Effective Learning Tasks*: number of correct maths tasks over study (inc. distractors ignored).

The *Total Learning Time* (i.e. traditional 'time-on-task') for the study was around 200 minutes for each participant (20 minutes a day for 10 days). We

hypothesized that *Effective Learning Time* and *Effective Learning Tasks* would predict *Learning Gains*, but that *Total Learning Tasks* would not.

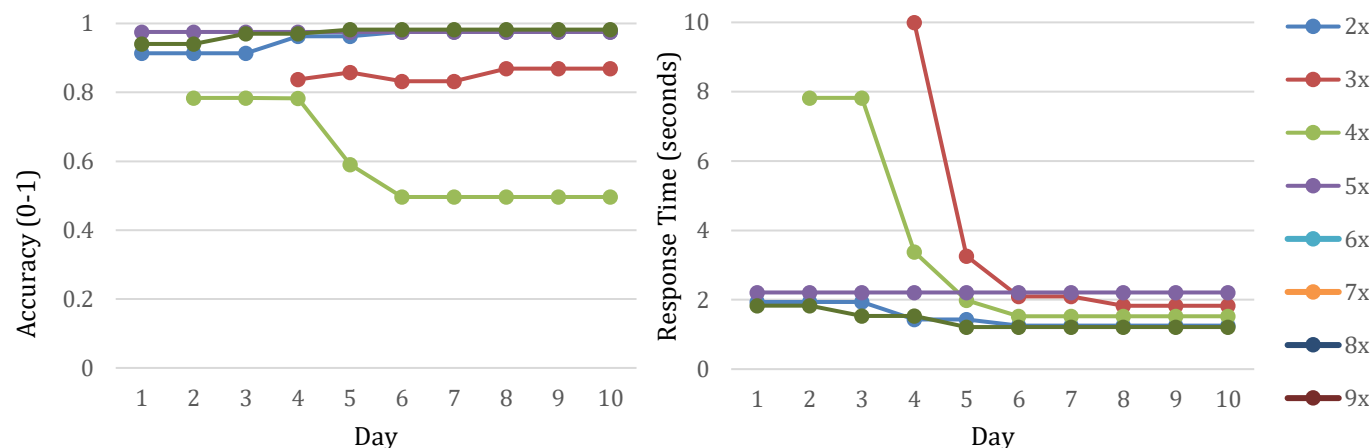
Results

The measures above were investigated for correlations with Learning Gains. Of the 53 children that took part in the study, seven missed the final test and one tablet's data was corrupted. Six were excluded from the analysis because of sub threshold pre-test scores or Learning Gains above or below twice the standard deviation from the mean. *Learning Gains* were found to be significantly correlated with *Effective Learning Time* ($r(39) = 0.324$, $p=0.044$), *Effective Learning Tasks* ($r(39) = 0.492$, $p=0.001$) and *Total Learning Tasks* ($r(39) = 0.327$, $p=0.042$), but not *Total Learning Time*.

Response Times and Accuracy

This result suggests that, despite the intrinsically integrated design, Effective Learning Time is not the strongest predictor of learning gains in the current version of the RAIDING game. Furthermore, as Effective Learning Tasks is a stronger predictor of learning outcomes, it suggests that some players may not be spending their time productively in the mathematical mining games. To examine this further we used the analytical data collected by the game to plot each child's accuracy and response times as recorded by the learner model over the course of the intervention. While many players demonstrated the desired increases in speed and accuracy over the length of the study, others exhibited a reduction in accuracy at the expense of improved response times. For some players this change was quite rapid and seemed indicative of a change in behaviour (see figure 2).

Figure 2: An individual player's accuracy (left) and response times (right) for each times-table (colours) as recorded by the learner model over the course of the study.



Data-Driven Game Design

The findings of this investigation have led the RAIDING team to reconsider the design of the reward system included in the game for improving response times. Currently there is no equivalent penalty for a reduction in accuracy, thus encouraging some players to make responses quickly without engaging with the mathematical content. The data-driven analysis described in this paper has allowed us to identify and address this flaw and introduce an equivalent penalty for incorrect responses (extinguishing flaming rocks in the mining cart). In this way we hope to encourage both speed and accuracy and keep players productively engaged with the game's mathematical content.

References

1. Carroll, J. B. 1963. A model of school learning. *Teachers college record*.
2. Habgood, M. J. and Ainsworth, S. E. 2011. Motivating children to learn effectively: Exploring the value of intrinsic integration in educational games. *Journal of the Learning Sciences*, 20, 2: 169-206.

3. Kovanović, V., Gašević, D., Dawson, S., Joksimović, S., Baker, R. S. and Hatala, M. 2015. Penetrating the black box of time-on-task estimation. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge*, 184-193.
4. Luton, W. *Free-to-play: Making money from games you give away*. New Riders, 2013.
5. Mees, M., Jay, T., Habgood, J. and Howard-Jones, P. 2017. Researching adaptivity for individual differences in numeracy games. In *Extended Abstracts Publication of the Annual Symposium on Computer-Human Interaction in Play-CHI PLAY'17 Extended Abstracts*, 247-253.
6. Romero, M. and Usart, M. Time factor in the curriculum integration of game-based learning. In *Anonymous New pedagogical approaches in game enhanced learning: curriculum integration*. IGI Global, 2013, 248-266.